This is a post-peer-review, pre-copyedit version of an article published in Agricultural Systems. The final authenticated version is available online at: https://doi.org/10.1016/j.agsy.2017.01.016

Title: Combined effects of climate change and policy uncertainty on the agricultural sector in Norway

Authors: Klaus Mittenzwei, Tomas Persson, Mats Höglind, Sigrun Kværnø

Affiliation: Norwegian Institute of Bioeconomy Research (NIBIO), Postboks 115, NO-1431 Ås

Corresponding author: klaus.mittenzwei@nibio.no

Abstract

Farmers are exposed to climate change and uncertainty about how that change will develop. As farm incomes, in Norway and elsewhere, greatly depend on government subsidies, the risk of a policy change constitutes an additional uncertainty source. Hence, climate and policy uncertainty could substantially impact agricultural production and farm income. However, these sources of uncertainty have, so far, rarely been combined in food production analyses. The aim of this study was to determine the effects of a combination of policy and climate uncertainty on agricultural production, land use, and social welfare in Norway.

Output yield distributions of spring wheat and timothy, a major forage grass, from simulations with the weather-driven crop models, CSM-CERES-Wheat and, LINGRA, were processed in the a stochastic version Jordmod, a price-endogenous spatial economic sector model of the Norwegian agriculture. To account for potential effects of climate uncertainty within a given future greenhouse gas emission scenario on farm profitability, effects on conditions that represented the projected climate for 2050 under the emission scenario A1B from the 4th assessment report of the Intergovernmental Panel on Climate Change and four Global Climate Models (GCM) was investigated. The uncertainty about the level of payment rates at the time farmers make their management decisions was handled by varying the distribution of payment rates applied in the Jordmod model. These changes were based on the change in the overall level of agricultural support in the past. Three uncertainty scenarios were developed and tested: one with climate change uncertainty, another with payment rate uncertainty, and a third where both types of uncertainty were combined. The three scenarios were compared with results from a deterministic scenario where crop yields and payment rates were constant. Climate change resulted in on average 9 % lower cereal production, unchanged grass production and more volatile crop yield as well as 4 % higher farm incomes on average compared to the deterministic scenario.

The scenario with a combination of climate change and policy uncertainty increased the mean farm income more than a scenario with only one source of uncertainty. On the other hand, land use and farm labour were negatively affected under these conditions compared to the deterministic case. Highlighting the potential influence of climate change and policy uncertainty on the performance of the farm sector our results underline the potential error in neglecting either of these two uncertainties in studies of agricultural production, land use and welfare.

Keywords: climate change, Norway, agriculture, policy uncertainty, modelling, LINGRA, CSM-CERES-Wheat, DSSAT

1. Introduction

Current research on climate change has led to a renewed interest in uncertainty as an increasingly important factor in any study that attempts to assess the effects of climate change on agricultural production (Olesen *et al.*, 2007; Lobell and Burke, 2008; Asseng *et al.*, 2013). This is because the impacts of climate change, notably those related to higher variance of weather distributions are not yet fully understood (Thornton *et al.*, 2014). Such an increased variability in the weather distributions could entail increased risks of losses in the agricultural production sector due to increased frequency and intensity of heat waves and dry spells, especially in regions which already today experience warm and dry conditions (Bindi and Olesen, 2011; Teixeira *et al.*, 2013). For the agricultural sector in northern Europe, positive effects including a prolonged growing season and increased crop yields from projected climate change have been projected (Bindi and Olesen, 2011; Rötter *et al.*, 2012) although the range in climate projections also allow for negative yield effects (Rötter *et al.*, 2012). However, potential effects of the projected climate change with increased weather variability on the agricultural sector in this region, including effects on farm profits and welfare, have been given little attention so far.

Farm income in many countries depends to a large extent on various types of farm subsidies (OECD, 2014). Hence, farmers are exposed to uncertainties regarding the design and extension of these subsidies. That policies themselves constitute a source of risk to farmers is commonly underemphasized in research (Gardner, 2002). While some studies focus on farmers' perceptions and responses to policy risk (Flaten *et al.*, 2005; Niles *et al.*, 2013), we are not aware of any study that explicitly compares the effects of the two different sources of uncertainty on the agricultural sector: climate change and policies. Previous analyses of impacts of climate change on farm productivity have assumed present day prices also under projected future climate conditions (Leclère *et al.*, 2013). The farming sector in Norway, which is dominated by forage grass based dairy, beef and sheep production, and primarily in the southern regions, to some extent also include spring and winter cereals for bread or animal feed, is heavily dependent on governmental subsidies. Currently, at the farm sectoral level about two-thirds of farm income in Norway is related to policy interventions in form of market price support and subsidies, which is a high proportion compared to other countries (OECD, 2014). The significant dependence of subsidies on farm-income in Norway constitutes a potentially important source of uncertainty as policies, in principle, can shift frequently. Subsidies have remained fairly stable over the last decades, however, because there has been broad parliamentary support for the need of agricultural policies to achieve agricultural policy goals such as a high level of self-sufficiency (Ministry of Agriculture and Food, 2011).

While decision-making under risk at the farm level has been widely analysed (Hardaker *et al.*, 2004), studies taking into account uncertainty at the sectoral level are less common as many agricultural models at that level are deterministic (Van Tongeren *et al.*, 2001). Moreover, the analysis of the combined effects of uncertainty due to projected climate change and due to potential shifts in agricultural policies that farmers are facing could help better understand the prospects of agricultural production until the mid-21st century and the need for adjusting agricultural policies. Accordingly, the results from such an analysis could help to develop new strategies to handle the uncertainty that such climate and policy changes are associated with on farm and national levels. The relatively high dependency of the profitability of the farm sector in Norway on farm subsidies makes this country a suitable object for a study of the combined effects of climate and farm policy uncertainty on farm profit, production, land use and other performance indicators of the agricultural sector. Such a study could help clarify the effect various sources of uncertainty have on the agricultural sector and hence help guiding research needs, policy focus and farm management towards the source with the largest adverse impact.

Models aimed at understanding the impact of various exogenous variables on agricultural systems have been developed during the last decades. These models include, among other models, agricultural sector models (Takayama and Judge, 1971; Van Tongeren *et al.*, 2001), and dynamic crop simulation models (Jones *et al.*, 2003; Keating *et al.*, 2003; Stöckle *et al.*, 2003). The former models simulate the response of farmers and other economic agents to changes in the model's exogenous variables like world market prices, technological progress and population growth. Such changes (or 'policy shocks') can be related to changes in agricultural or trade policies, in input or output prices or technologies. The objective of these models is to determine equilibrium prices and quantities in markets that are endogenous to the model (Van Tongeren *et al.* 2001). Crop models simulate the effect of exogenous physical variables, such as the weather, soil characteristics and crop management practices, on the growth, development and yield of agricultural and horticultural crops during the growing season (Jones *et al.*, 2003; Keating *et al.*, 2003; Stöckle *et al.*, 2003). The latter type of models has previously been applied to assess crop potential under different geophysical conditions including those representing climate change (Soussana *et al.*, 2010).

Linking models of different scope and scale, such as economic and biogeophysical agricultural models, is a complex task (Ewert *et al.*, 2011). There are nevertheless a few notable examples of such linkages. Briner *et al.* (2012) studied the impact of climate change on agricultural ecosystems using a modular framework including an economic land allocation model and a crop model. Their approach was dynamic, but did not involve uncertainty.

Lehmann *et al.* (2013) studied the impact of climate and price risk in Swiss agriculture by combining a whole-farm bioeconomic model and a crop growth model. Although accounting for climate and price uncertainty, their approach was related to the farm rather than the agricultural sector.

The use of crop model output yields resulting from simulations under current and projected future climate conditions as input to a farm sector model, which, in turn, is run under contrasting policy scenarios would be one adequate approach to determine and compare the effects of climate and policy uncertainty on farm profits and welfare. Even though there are crop simulation studies, which include climate change conditions published for most regions of the world (White *et al.*, 2011), the data are usually not suitable for direct use in economic models. Mostly, only average yield data, which are not sufficiently detailed to account for the variability that is relevant to include in an analysis of climate change impact on the profitability and welfare of the agricultural sector, are available from previous studies. In addition, the crops included in such simulations usually do not represent the mix of crops which is typical for production systems in a region, but are rather chosen to evaluate climate change effects on a specific crop. Therefore, crop simulations with the aim of generating yield data that would be further processed in economic models should be tailored to the framework and the aim of the simulations with the economic models. A study with such an approach would also extend previous work on risk handling at farm level by including a stochastic model in which farmers make management decisions in the presence of uncertainty about yields and payment rates of agricultural subsidies.

The aim of this study was to determine the effects of a combination of policy and climate uncertainty on agricultural production, land use, and social welfare in Norway. Those characteristics are important in order to measure to which extent agricultural objectives in Norway are achieved and thus to identify and implement possible measures to alleviate negative consequences of policy and climate uncertainty. The remainder of the paper is outlined as follows. A description of the crop models and the economic model is given in the next section. Section 3 introduces the modelling framework, while scenarios are presented in section 4. The main results of the study can be found in section 5. The final section discusses the results and concludes the paper.

2. Model description

In this study, we applied two crop simulation models, the CSM-CERES-wheat model (Ritchie *et al.*, 1998) as included in the Decision Support System for Agrotechnology (DSSAT) v 4.5 software (Hoogenboom *et al.*, 2010) and timothy grass version of the LINGRA model (Höglind *et al.*, 2001), and the Jordmod farm sector model (Brunstad *et al.*, 2005) to evaluate the combined effect of climate change and related uncertainty, and policy related uncertainty on key characteristics of the agricultural sector in Norway until 2050. These characteristics included crop, milk and beef production and farm profitability.

2.1. Crop simulation models

The CSM-CERES-Wheat and the LINGRA model dynamically simulate growth, development and yield of wheat and timothy grass, respectively, as a function of weather, soil, and crop management practices over the growing season with a time step of one day. Parameters, which regulate growth and development functions in these models, are calibrated to represent cultivar specific traits. Both models are based on the source-sink concept, where photosynthesis and mobilization of reserves represents sources, and sinks constitute growth and respiration of plant tissues. LINGRA is able to simulate the removal of the above-ground biomass in the form of cutting and harvesting in production systems with multiple seasonal cuts. The partitioning of biomass between plant organs are modified by stresses in form of sub-optimal temperatures, water deficit, and, for the CERES-wheat model, also nitrogen deficit. LINGRA assumes optimal nitrogen supply and does not directly take into account any impact of sub-optimal nitrogen supply. Daily weather input data to the simulations include minimum and maximum air temperature, precipitation and solar radiation. Soil input data include soil water characteristics such as water content at saturation, field capacity and wilting point. The LINGRA model represents soil in one single layer, whereas the CSM-CERES-wheat model handles multiple soil layers (Ritchie, 1998). For more details about the CSM-CERES-Wheat model see Ritchie *et al.* (1998), and for more details about the LINGRA model see Schapendonk *et al.* (1998) and Höglind *et al.* (2001).

2.2 Jordmod

Jordmod is a price-endogenous, spatial, comparative-static, and partial equilibrium model for the agricultural sector in Norway (Brunstad *et al.*, 2005; Bullock *et al.*, 2016). It consists of two modules: a supply module and a market module. The supply module comprises optimization models for farms and for the food industry. The farm optimization models generate input-output coefficients for eleven farm types in thirty-two regions by maximizing farm income. Outputs include crops like wheat, rye, barley and oats as well as milk, meats and eggs. Inputs cover labour, capital, and intermediate inputs like feed and manure. The maximization procedure is subject to fixed input and output prices, Leontief technology for intermediate inputs, non-linear cost functions for labour and capital, and subsidies with partly non-linear payment rates. Crop management practices are modelled through yield-independent costs for inputs such as pesticides and machinery. Agronomic practices like feed requirements, crop rotations and fertilizer needs are accounted for. The responses of cereals and grass yields to nitrogen fertilizer inputs are modelled as non-linear with diminishing returns, as is the relationship between milk yields and feed quantity.

Agricultural policies in Norway can change every year. Policy measures are negotiated every spring between the government and the farmers' organizations. The negotiations cover *inter alia* the design of agricultural policies (i.e., eligibility criteria and payment rates) and producer prices for milk and cereals. Producer prices are adjusted in July the same year so that farmers in principle do not know actual cereal prices when making planting decisions in the fall the year before. Subsidies are linked to output (milk and meat, but no crops) and input (e.g., number of animals, acreage). The payment rates negotiated in one year apply to the following year so that farmers know the actual payment rates when making planting decisions in the fall. Payment rates differ by region and farm size. Milk quotas are in place for dairy production from cattle and goats. Norwegian farmers are protected from foreign competition through import tariffs, which are not part of the annual agricultural negotiations.

Many factors play a role in determining the annual agricultural policy package. Negotiators respond to agricultural policy objectives decided by the parliament. For example, the current focus of Norwegian agricultural policy to increase domestic food production is mirrored in the increase of output-based support. Other factors include the development of the farm sector in terms of food production, land use and farm income, general economic conditions, and political considerations, for example in election years.

The food industry optimization models minimize total industry costs related to volume and regional distribution of raw commodities, transport costs between farms and processing plants, and processing costs at the plants. Raw commodities are processed into products for final demand by specialised firms.

The market module consists of 41 final markets. The supply part of the final markets consists of identical farms for each type and region, as well as food industry firms, whose number is determined in equilibrium. Final demand enters through linear demand functions that are calibrated to base year levels (2011). Trade occurs with the rest of the world at fixed world market prices. Trade policies such as import tariffs, import quotas and export subsidies apply. The objective function of the model maximizes social welfare of the agricultural sector comprising producer surplus, consumer surplus and importer surplus (net of import tariffs). Since the model is partial, budget support to agriculture is part of the sector's welfare.

Jordmod is deterministic in nature. In order to cope with climate and policy uncertainty, the farm optimization models have been further developed for this study to handle stochastic decision making. Farm optimization follows stochastic scenario method. Risk-averse farmers make decisions under uncertainty in an otherwise deterministic environment. More specifically, farmers make decisions two times during a model simulation. At the first instance, crop planting decisions with regard to the crop mix and nitrogen fertilizing intensity is made under uncertainty regarding yields and payment rates. Eq. (1) shows the farmer's objective function using a mean-variance formulation:

$$(1) \quad E(U|\theta,\vartheta) \equiv \max_{\boldsymbol{y},\boldsymbol{x}} M\big(\pi(\boldsymbol{y},\boldsymbol{x}|\boldsymbol{p},\boldsymbol{w},\theta,\vartheta)\big) - 1/2 \cdot \delta \cdot V\big(\pi(\boldsymbol{y},\boldsymbol{x}|\boldsymbol{p},\boldsymbol{w},\theta,\vartheta)\big),$$

where $E(U|\theta,\vartheta)$ is expected utility with θ being a stochastic weather variable with a discrete distribution τ_n and probability q_n while ϑ being a stochastic policy variable with a discrete distribution σ_n and probability ρ_n. Farm profit is denoted by $\pi(\boldsymbol{y},\boldsymbol{x}|\boldsymbol{p},\boldsymbol{w},\theta,\vartheta)$ where $\boldsymbol{p}$ is a vector of exogenous output prices, $\boldsymbol{w}$ is a vector of exogenous input prices, $\boldsymbol{y}$ is a vector of decision variables like crop activities and nitrogen intensities, and $\boldsymbol{x}$ is a vector of decision variables like livestock activities and feeding systems. $M(\pi)$ and $V(\pi)$ denote mean profit and variance of the profit, respectively. Finally, δ denotes the risk aversion coefficient.

In the first step, nature resolves uncertainty both with regard to yields and subsidy rates. Nature's choice is depicted by a pair (θ^n,ϑ^n). In the second step farmers adjust their number of ruminants and/or the feeding intensity with regard to the amount of fodder they have harvested (eq. (2)). This optimization is similar to Eq. (1), besides that, as (θ^n, ϑ^n) is now known, farmers simply maximize profits for given yields and payment rates.

$$(2) \quad U \equiv \max_{\boldsymbol{x}} \ \pi(\boldsymbol{x}|\boldsymbol{y}, \boldsymbol{p}, \boldsymbol{w}, \theta^n, \vartheta^n)$$

As in the deterministic version of the model, the farm optimization models generate input-output coefficients that comprise the supply part of the market module. Hence, only producers face uncertainty in the model.

The model's data stem from various sources. Most important are the economic accounts of agriculture (BFJ, div.) for physical and monetary input and output, the direct payment register for animal numbers and crop area for individual farms (Norwegian Agriculture Agency, div.), and the farm account statistics to disaggregate inputs and outputs (NIBIO, div.).

3. Modelling framework

To analyse the effect of climate and policy uncertainty on crop yields, agricultural production, land use and social welfare, a modelling framework with contrasting scenarios with respect to the climate and policy were set up as described below. For this analysis, Jordmod, the two crop models LINGRA and CSM-CERES-wheat and scenarios and data about climate, farm management and poli

[Figure 1 about here]

Each scenario consists of $N \times N$ single Jordmod model runs with probabilities $\tau_1, \dots, \tau_N$ and $\rho_1, \dots, \rho_N$. Taken together, the model runs create a "pseudo-stochastic" distribution of social welfare W which is the model's objective $\mathrm{W}(\boldsymbol{x}|\boldsymbol{y}^{\boldsymbol{\theta}_1\boldsymbol{\vartheta}_1}, \boldsymbol{p}, \boldsymbol{w}, \boldsymbol{b}), \dots, \mathrm{W}(\boldsymbol{x}|\boldsymbol{y}^{\boldsymbol{\theta}_N\boldsymbol{\vartheta}_N}, \boldsymbol{p}, \boldsymbol{w}, \boldsymbol{b}),$

where ***b*** is a vector of market parameters such as elasticities of demand functions, initial amount of demand, transportation costs, and population growth. The number of model runs was chosen so to balance the need for spanning out a reasonable wide parameter range and the need for keeping the number of number of model runs at a limited level due to the time-consuming computations. Five model runs were chosen ($N = 5$), which gives a maximum of 25 model runs for each scenario. The five discrete points are picked at both one time and three times the standard deviation in both directions in addition to the mean. The points were picked for grass yields, wheat yields and payment rates. In absence of better information, a uniform probability distribution across the five discrete points is assumed.

4. Scenarios

Three scenarios were developed to shed light on the impact of climate and policy uncertainty on producers, consumers and the agricultural sector as a whole: “climate” (C), “policy” (P), and “climate and policy” (C&P). The climate uncertainty scenario (C) studies the distinct impact of uncertainty that is associated with climate projections within a given future increase of greenhouse gas emissions on crop yield. Potential direct climate impact on animal production is not taken into account. Policy uncertainty is removed and payment rates set at their mean values of the past years as described below. Thus in this scenario, five model runs are necessary to span out the distribution of social welfare W. Similarly, the policy scenario (P) analyses the consequence of policy uncertainty while setting the yields equal to the mean of the yields that were simulated under different climate and weather conditions representing projections of the climate for the period 2046-65 as described below. Again, five model runs are necessary to span out W. Consequently, the combined climate and policy scenario, C&P,

studies the combined effects of both climate and policy uncertainty. To span out *W*, all 25 Jordmod model runs were necessary.

In order to include the impact of climate uncertainty within a given future greenhouse gas emission scenario, in the scenario analysis, we first conducted wheat and timothy grass simulations with the CSM-CERES-wheat and LINGRA models respectively. The wheat simulations with the CSM-CERES-Wheat model were part of simulations that were previously included in a study of regional spring wheat yields in South-Eastern Norway (Persson and Kværnø 2016). Yields of the cultivars Bjarne, Demonstrant and Zebra, which are all among the most commonly grown spring wheat cultivars in Norway, were simulated. In the timothy grass simulations, we used a set of parameter values which represented the cultivar Grindstad as calibrated by Persson et al (2014) for conditions which represent the Nordic countries of Europe. Timothy grass was simulated for climate conditions, which represent Ås, Akershus county, (59°40′ N; 10°48′ E; 89 m asl), Sola, Rogaland county, (58°53′ N; 5°38′ E; 7 m asl), Tromsø, Troms county (69°41′ N; 18°55′ E; 100 m asl) and Værnes, Nord-Trøndelag county (63°27′ N; 10°55′ E; 12 m asl), whereas spring wheat was only simulated for the first location. This division followed the current geographical distribution of the production of forage and cereal crops in Norway. Daily weather input data to the crop models including maximum and minimum air temperature, precipitation and solar radiation, which represented the climate for the period 1961-1990 and projections of the climate for the period 2046-2065, the greenhouse gas emission scenario A1B from the Special Report on Emission Scenarios (SRES) (Nakicenovic *et al.*, 2000) and four global climate models (GCM) BCM2.0, CSIRO-M.k3.0, GISS-AOM and HadCM3, which are all included in the Intergovernmental Panel on Climate Change (IPCC) 4th assessment report (Pachauri and Reisinger, 2007). For the generation of daily weather data that represented these periods and projections the Long Ashton Research Station Weather Generator (LARS-WG) tool

(Semenov, 2010) and historical reference weather data from weather stations of the Norwegian Meteorological Institute were applied. In total, for each GCM and the historical reference climate, the LINGRA and CSM CERES-wheat models were run for 100 years of independent and stochastic daily data minimum and maximum air temperature, precipitation, global solar radiation and evapotranspiration. The average of these weather variables as well as the variation differed among the five generated weather datasets. The reason for the choice of GCM in the generation of daily weather data was the following. The 100 years of independent data were considered a sufficient sample of stochastically generated weather data to include most of the probable weather variability within each GCM. Weather data generated from these four GCMs resulted in timothy grass yield in the lower, centre and upper section of the entire range of timothy grass yields in northern Europe that were simulated with the LINGRA model and weather input data generated from 15 GCM and the A1B greenhouse gas emission scenario for the period 2046-65 (Höglind *et al.*, 2013). Therefore, we considered these four GCMs representative to cover the range of yield uncertainty under the A1B scenario also in this study.

The carbon dioxide level in air was set to ambient levels (380 ppm) for the simulation of the period 1961-1990 and set to 532 ppm for all the simulations where weather data that represented the period 2046-2065 were input. The latter CO_2-concentration represents the A1B greenhouse gas scenario for this period in the IPCC 4th assessment report. Soil data including hydraulic characteristics such as water content at wilting point, field capacity and saturation that were input to the two crop models represented a siltic Luvic Stagnosol, which is the most common soil type in in southeastern Norway according to the national soil database (Forest and Landscape Institute 2014). Previous analysis of the impact of simulated timothy grass (Persson et al 2015) and spring wheat (Persson and Kværnø 2016) showed that differences in the soil input data had little effect on the regional biomass and grain yield under current and projected future climate conditions. Therefore, we did not include more than one soil even though both crops are grown on several types of soils in Norway. Simulated wheat planting time and density, and nitrogen fertilizer rates represented normal practices for the region in question. The planting of wheat under the projected future climate conditions was adjusted so that it occurred when the average mean air temperature was the same as under the historical baseline scenario. For more details about the spring wheat simulation settings see Persson and Kværnø (2016). The timothy growth was set to start the fifth day the first time of the year the average air temperature exceeded 5˚C for at least five consecutive days. The first harvest in the season was set to occur after a temperature sum of 500 °days (above 0˚C) from the start of the growing season. Later harvests were set to occur each time the temperature sum (above 0˚C) reach 600˚Cdays. This represents a harvesting schedule, which aims at yield quantities and qualities, which are suitable for dairy cows at the current average milk production level in Norway.

The simulated grass and spring wheat yields were subsequently calibrated to fit the yield functions of the Jordmod model. As described above, the simulated yields were influenced by soil and climatic variables, but exposed to the same level of nitrogen. On the contrary, the yields for grass and cereals in the economic model vary with nitrogen input. In the base year and for the given nitrogen level, a comparison of the grass yields between LINGRA as simulated for the 1961-1990 climate and reported grass yield from statistical Norway, which were previously used in Jordmod indicated a yield gap of 36 – 58 per cent depending on the region. A yield gap between simulated crop yields and average regional statistical yields of similar magnitude has been confirmed in other studies. For instance, the Global Yield Crop Altas (2015) indicates a yield gap of 40 – 50 (30 – 40) per cent for rainfed barley in Denmark and Germany, respectively. For the yield that was assessed under climate projections for the mid 21st century, the same relative yield gap was applied. The relative yield changes for timothy grass due to climate change were assumed to represent also other perennial forage crops that are grown in Norway. The simulated timothy grass yields for each location were adjusted and applied to the regions included in the economic model according to the following division. Timothy grass yields that were simulated for Sola were used to represent the South-Western lowlands (Jæren), yields simulated for Ås were used to represent the South-Eastern lowlands, Værnes yields were used to represent other regions in South-Eastern Norway, Western Norway and lowlands in Central Norway, and Tromsø yields were used to represent other regions in Central Norway and Northern Norway. Regarding cereals, the simulated yields from CSM-CERES-Wheat under the 2046-65 climate conditions for Ås were used to calculate the five discrete points of the yield distribution. The original yield functions in Jordmod for wheat, rye, barley and oat were then adjusted with the relative distance of these points from the simulated mean yield for all four set of weather data representing the four GCMs in CSM-CERES-Wheat. This implied an 11 per cent increase in the mean yields for cereals in 2050 in the economic model compared to the base year.

The stochastic levels of the direct payments are based on the past development of budget support to agriculture. The variation in the total amount of budget support for the years 2000 and 2013 in Norway in real terms was used to construct a distribution from which the mean and the standard deviation could be derived. For example, one standard deviation is ± 4.3 per cent around the mean. The deviation around the mean was used as an application factor for each payment rate in the model. That is, farmers face policy uncertainty through a uniform reduction or increase in all subsidy rates. The scenario outcomes are contrasted with the results of a single model run denoted “certainty” in which the mean yields and mean payment rates are applied with certainty.

Since Jordmod is comparative-static, it has no explicit time dimension. However, in order to shift the model’s exogenous parameters to some point in the future, a specific year is assumed. The period of 2046-65 that were used for crop simulation under projected climate conditions, cannot be applied to Jordmod, because there is too much uncertainty about the future development of core exogenous parameters. Therefore, a medium-range timeframe of 19 years was assumed, which makes the exogenous parameters other the crop yields to represent the year 2030 in all Jordmod simulations. Exogenous variables are projected using the values shown in Table 1. Technical progress is modelled as an annual reduction in input costs independent of changes in yields, which respond only to a change in the level of nitrogen. Input costs cover seed, plant protection, mineral fertilizer, veterinary services, feed concentrate, maintenance, electricity, fuel and other variable costs.

[Table 1 about here]

5. Results

5.1 Crop model results

Both the simulated seasonal timothy grass yield and the spring wheat grain yield were significantly higher ($p<0.05$) under the projections of the 2046-2065 climate conditions than under the baseline 1961-1990 climate scenarios. The only exception was the non-significant difference between the timothy grass yield under the baseline scenario and the 2046-2065 climate projection based on the GCM GISS-AOM. There was no consistent trend in the difference in the average simulated timothy yield between the climate projections across the locations. The average simulated grain yield of spring wheat was higher under the 2046-2065 climate projection based on the GCM HADCM3 than under the other GCMs, across the three cultivars. It is noticeable that the timothy grass yield that were simulated with weather data based on the GCM HADCM3 at the same location was lower than the yields that were simulated with weather data based on the other GCM (Table 2 and 3).

[Table 2 about here]

[Table 3 about here]

5.2 Economic model results

Climate uncertainty and policy uncertainty had quite different impact on production, input use, agricultural income and welfare of the agricultural sector as shown below. The following figures and tables report the maximum value, the minimum value, the mean and the standard deviation for selected results of the economic model. Crop production was more heavily affected than animal production. Interestingly, cereals were more sensitive to climate uncertainty than grass (Figures 2 and 3).

[Figure 2 about here]

Climate uncertainty caused a large variance in cereals production even in the absence of policy uncertainty. The lowest value of cereals production (217,000 t) was about one fifth of the mean value, while the highest value was 50 per cent higher than the mean value. Policy uncertainty had only a minor effect on cereal production. The main reason is that profitability remains positive despite of the reduced support, as further explored below. Grass production was much less affected by climate uncertainty than cereal production. The same was true regarding policy uncertainty.

[Figure 3 about here]

Animal production was far less affected by uncertainly than crop production (Table 4). Uncertainty about payment rates had a lesser effect on the amount of milk production than uncertainty about grass yields. Regarding milk production, the main reason was that milk quotas prevented milk production to increase when payment rates got higher or yields increased. Fodder production accounts only for roughly 25 per cent of the total costs of milk production (REF). Profitability ensured production to fall significantly even when grass yields or payment rates were lowered. In the scenario where both climate and policy were uncertain, profitability contributed to minor changes in the mean milk production. Meat production, comprising beef, sheep, pork and poultry, was somewhat more affected compared to milk production, but still considerably less than crop production. Mean meat production was slightly higher in the scenario with combined climate uncertainty and policy uncertainty compared to the certainty scenario and when farmers faced one source of uncertainty only. Climate uncertainty and policy uncertainty alone had almost the same effect.

[Table 4 about here]

In order to better understand the results on meat production, Table 5 decomposes meat production into the production of beef and sheep (red meat) and pork and poultry (white meat). Red meat was slightly negatively affected by either source of uncertainty as well as by a combination of the two. On the contrary, white meat expanded in all three scenarios compared to the certainty situation. Climate uncertainty and policy uncertainty reinforced each other in the case of red meat production as can be inferred from the standard deviations. A combination of yield and payment rate increase (row "max" in Table 5), improves profitability and leads to higher production, but still within the limit of milk quotas regarding beef production from dairy cows. The opposite (row "min" in Table 5) is true as well.

[Table 5 about here]

Being a production not directly depending on land, white meat is only indirectly affected by climate change. The increase of white meat production under climate uncertainty is caused by lower feeding costs due to yield changes. Per unit feeding costs decline as mean cereal yields increase without a corresponding increase in cereal production costs. Policy uncertainty has a direct effect on white meat production through the change in payment rates. However, the effect of policy uncertainty was smaller than the effect of climate uncertainty. White meat production receives far less direct subsidies than red meat production, and therefore a change in payments had a lower effect on the profitability of white meat production. As for red meat production, a combination of climate uncertainty and policy uncertainty reinforced each other in expanding white meat production.

Input use closely followed production (Table 6). Climate uncertainty had a larger effect on total agricultural area than had policy uncertainty. The large effect of climate uncertainty on cereal production was counteracted by the smaller effects on grass production so that the variance for agricultural area was much smaller than for cereal production alone. Although the mean agricultural area was mainly the same in the three scenarios, the combination of climate uncertainty and policy uncertainty increased the variance. Agricultural area was hardly increased even under favourable climatic and political conditions compared to the fixed average climate and policy scenario, while it fell significantly under unfavourable conditions. That is due to the fact that agricultural area in Norway is scarce and current use covers about 90 per cent of the area that potentially could be taken into agriculture.

[Table 6 about here]

Labour exhibits a similar picture. Person-years in agriculture are lowest when climate uncertainty and policy uncertainty are combined.

Table 7 presents two profitability measures: land rents and rents on milk quotas. The effect of climate uncertainty and policy uncertainty on land rents was ambiguous. On the one hand, the mean value was somewhat higher under policy uncertainty compared to climate uncertainty. On the other hand, policy uncertainty caused land rents to become much more volatile compared to climate uncertainty. In the C&P scenario, the maximum land rent (6 324 Nkr per ha) was about 3.5 times higher than the minimum land rent (1 811 Nkr per ha). Although land rents dropped, they did not fall to zero indicating continued profitability in farming. This explains why production, and input use, was not harder affected by climate uncertainty or policy uncertainty.

[Table 7 about here]

Milk quota rents stayed fairly robust compared to land rents. The maximum value in the C&P scenario was only 20 per cent higher than the minimum value. Contrary to land rents, quota rents were more exposed to volatility by climate uncertainty than by policy uncertainty.

Finally, Table 8 shows the impacts on agricultural income and social welfare. When measured per person-year, both climate uncertainty and policy uncertainty increased the mean income to a similar extent. However, volatility was higher under climate uncertainty. This result is somewhat in contrast to the effects on land rents that were more exposed to policy uncertainty than climate uncertainty. An important reason for this result is the change in the production patterns in the scenarios. A decrease in cereal production increased the mean level of agricultural income per person-year because cereal farmers achieve low incomes compared to, for example, dairy farmers. As the number of cereal farmers shrank under climate uncertainty due to lower production, the average income per person-year increased.

The mean income was highest when climate uncertainty was combined with policy uncertainty, but volatility remained quite high. When both sources of uncertainty were combined, the highest income was about 25 per cent higher than the lowest income. This difference fell to about 15 (8) per cent when climate (policy) uncertainty was concerned. On the contrary, social welfare at the sector level remained quite stable. In all three scenarios, the highest value of social welfare was at most 3 per cent higher than the lowest value.

[Table 8 about here]

Consumer surplus takes the largest part of social welfare. Under the model's assumption of well-functioning trade and international markets, climate and policy uncertainty had little effect on Norwegian consumers. A drop in domestic production can be compensated for by more imports. Regarding cereals, an increase in domestic production due to more favourable climate conditions, reduces the requirement for imports.

6. Discussion and conclusion

The study comprised an analysis of the combined effects of various sources of uncertainty on agriculture. By constructing scenarios where we allowed policy to vary within certain ranges and the climate to vary within the uncertainty of a given greenhouse gas emission scenario, we were able to assess the effects on the agricultural sector caused by such variability. The results indicated that uncertainty about future yields can have as significant effects on production, land use and farm income as uncertainty about future payment rates. The climate change projections that were included in this study led to higher simulated yields, even though these yields varied due the uncertainty associated those projections, which translated into higher simulated income for the average farmer. Average income was about the same in the scenario where the policy varied as in the scenario where the climate varied. Higher income variance in this scenario than policy uncertainty however indicates that climate change causes more uncertainty to future farm income than uncertainty in policy within the frame of this study. The benefits of higher expected farm income due to climate change come with a cost of increased variance. In other words, even if farm income is expected to rise on average, it can also be expected that farm income will vary considerably more between years. This may call for policies that promote stable farm income by levelling farm income between years.

Another general conclusion is that we did not find clear evidence that one source of uncertainty is more important than the other, notwithstanding increased income uncertainty for crop famers. That result depended, of course, on the assumptions underlying the scenarios. Larger standard deviations might have led to a situation in which policy uncertainty dominated climate uncertainty. In fact, the assumption of unchanged border protection has kept policy uncertainty in our study at a considerably lower level compared to a situation where farmers were uncertain about the level of domestic producer prices. On the other hand, the potential effects of including uncertainty in world market prices with respect to climate change effects (e.g., Fischer *et al.*, 2002; Parry, 2004; Darwin, 2004) on changes on both producers and consumers would have been small.

The yield increase in this study agreed with the trend of positive effects of climate change on agricultural crop yields in northern Europe in previous studies (Rötter *et al.*, 2012; Höglind *et al.*, 2013; Rötter *et al.*, 2013; Persson and Höglind; 2014), which explored future climate conditions that partly differed from those investigated here. Hence, these agreements suggest that our findings about the relative importance of climate and policy uncertainty could be relevant under a broader range of climate projection than what we investigated.

Changes in world market prices are only imperfectly transmitted into changes in domestic prices. That is, Norwegian farmers do not receive price signals due to strong market regulation. As Norwegian consumers are wealthy (high income per capita in international comparisons), the effects of moderate changes in world market prices on the overall welfare of consumers are expected to be small. Still, a few factors should be mentioned that potentially could have affected the direction and strength of the models' endogenous variables such as production, land use and farm income.

Alternative assumption regarding greenhouse gas emission scenarios, choice of crops and cultivars and crop management practices could have resulted in different impacts on land area allocated for crop, animal production, farm profitability and welfare. In particular, the handling of crops and cultivars in this study disregards any possible effects on the relative suitability of different crops due to climate change. A warmer climate could, for example, result in partial replacement of timothy grass with higher yielding, but less cold tolerant forage crops such as perennial ryegrass or the warm-temperature dependent crop forage maize, and a substitution of higher yielding winter cereals for spring cereal, which potentially could magnify the positive effects of climate change on the forage crop yields that were found here.

We assumed that climate uncertainty and policy uncertainty are unrelated. A well-known reason for government intervention in agricultural markets is to reduce income risk to farmers. The effects of government intervention on production risks are well understood (see Just and Pope (2002) for a review). However, we argue that Norwegian agricultural policies have so far been little occupied with reducing the risk of climate change. Instead, they have been mainly focussed on keeping up domestic food production and maintaining agriculture in all parts of the country.

Our study was based on a static and basically deterministic equilibrium model. Although producers are exposed to uncertainty, the model still assumes that markets clear after uncertainty is resolved, implying that consumers behave in a world of certainty. A more sophisticated representation of consumer behaviour would include the modelling of (price) uncertainty in markets, thus, requiring a stochastic, dynamic setting. Such an approach would probably require a completely new type of model. Such a model could be able to deal with problems like stockholding in case of food shortage at the international market. However, we argue, again, that stockholding for national food security purposes is a minor aspect in

Norwegian agriculture due to the smallness of the country's population and the close political and economic ties to other European countries and North-America. In addition, expanding models with new features may lead to an overload and complexity that renders a thorough understanding and interpretation of the causalities that lead to given results impossible.

Finally, our analysis followed a cascade approach. That is, output from the crop models were used as input in the economic model, but there was no feedback from the economic model to the crop models. Nevertheless, the results of this study indicate that such linkages should be given priority in the development of more comprehensive economic-biogeophysical modelling approach. First, one could think of nitrogen intensity as a potential feedback mechanism as the use of nitrogen in cereal and grass production is endogenously determined in the economic model, but exogenous to the crop models. Such linkages could provide a promising venue for future research. Second, the profitability indicators for forage and cereal production that are provided by Jordmod could constitute a feedback which determines the choice of crop in a modelling framework which include crop models able to differentiate between high and low yielding forage and cereal crops respectively.

In total, this study was a first attempt to determine the combined effects of future climate and policy uncertainty on the farming sector in Norway. We kept the study within intermediate ranges of both climate and policy uncertainty. The higher sensitivity to both climate and policy uncertainty to producers compared to consumers indicates that adaptation measures to avoid negative effects of such uncertainty will have potentially greater benefits in the former group. One measure by farmers to decrease their uncertainty related to climate conditions could be to shift from the more climate sensitive cereal production to the less sensitive forage based animal production. Regarding policy uncertainty, farmers could reduce uncertainty by switching to productions that are less subsidized, but these are the ones that are often less profitable as well.

Acknowledgements

This study was funded by the Research Council of Norway and conducted within the framework of the Modelling European Agriculture with Climate Change for Food Security (MACSUR) knowledge hub in the Joint Programming Initiative for Agriculture, Climate Change, and Food Security (FACCE-JPI).

References

Norwegian Agricultural Agency. Div. Direct Payment Data Base. Oslo: Norwegian Agricultural Agency. [Annually updated database of all farmers applying for subsidies]

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P.J., Rotter, R.P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P.K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A.J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L.A., Ingwersen, J., Izaurralde, R.C., Kersebaum, K.C., Muller, C., Naresh Kumar, S., Nendel, C., O/'Leary, G., Olesen, J.E., Osborne, T.M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M.A., Shcherbak, I., Steduto, P., Stockle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J.W., Williams, J.R., Wolf, J., 2013. Uncertainty in simulating wheat yields under climate change. Nature Clim. Change 3, 827-832.

Bindi, M., Olesen, J., 2011. The responses of agriculture in Europe to climate change. Regional Environmental Change 11, 151-158.

Briner, S., Elkin, C., Huber, R., Grêt-Regamey, A., 2012. Assessing the impacts of economic and climate changes on land-use in mountain regions: A spatial dynamic modeling approach. Agriculture, Ecosystems & Environment 149, 50-63.

BFJ (Budget Committee on Agriculture) (div.). Totalkalkylen for jordbruket [Economic Accounts for Agriculture]. Annual publication. Oslo: Norwegian Agricultural Economics Research Institute.

Brunstad, R.J., Gaasland, I. and Vårdal, E. 2005.Multifunctionality of agriculture: an inquiry into the complementarity between landscape preservation and food security. European Review of Agricultural Economics 32: 469-488.

Bullock, D.S., Mittenzwei, K. Wangsness, P.B. 2016. Balancing public goods in agriculture through safe minimum standards. European Review of Agricultural Economics 43: 561-584.

Darwin, R. 2004. Effects of greenhouse gas emissions on world agriculture, food consumption, and economic welfare. Climate Change 66:191–238

Ewert, F., van Ittersum, M.K., Heckelei, T., Therond, O., Bezlepkina, I., Andersen, E., 2011. Scale changes and model linking methods for integrated assessment of agri-environmental systems. Agriculture Ecosystems & Environment 142, 6-17.

Fischer, G., Shah, M., Van Velthuizen, H. 2002. Climate Change and Agricultural Vulnerability, A Special Report Prepared as a Contribution to the World Summit on Sustainable Development (International Institute for Applied Systems Analysis, Laxenburg, Austria).

Flaten, O., Lien, G., Koesling, M. Valle, P.S., Ebbesvik, M. 2005. Comparing risk perceptions and risk management in organic and conventional dairy farming: Empirical results from Norway. Livestock Production Science 95: 11-25.

FAO (Food and Agriculture Organization of the United Nations). 2011. FAO Stat Food Balance Sheet.Rome: FAO.

Gardner, B. 2002. Risk created by policy in agriculture. pp. 489-510. In: Just, R.E. and Pope, R.D. (eds): A Comprehensive Assessment of the Role of Risk in U.S. Agriculture. New York: Springer.

Global Yield Gap Atlas. 2015. http://www.yieldgap.org/. Verified August 2016

Hardaker, J.B., Huirne, R.B.M., Anderson, J.R., Lien, G. 2004. Coping with Risk in Agriculture. CABI.

Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Boote, K.J., Hunt, L.A., Singh, U., Lizaso, J.I., White, J.W., Uryasev, O., Royce, F.S., Ogoshi, R.M., Gijsman, A.J., Tsuji, G.Y., 2010. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5 [CD-ROM]. University of Hawaii, Honolulu, Hawaii.

Höglind, M., Schapendonk, A., Van Oijen, M., 2001. Timothy growth in Scandinavia: combining quantitative information and simulation modelling. New Phytologist 151, 355-367.

Höglind, M., Thorsen, S.M., Semenov, M.A., 2013. Assessing uncertainties in impact of climate change on grass production in Northern Europe using ensembles of global climate models. Agricultural and Forest Meteorology 170, 103-113.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T. 2003. The DSSAT cropping system model. European Journal of Agronomy 18, 235-265.

Just, R.E., Pope, R.D. 2002. A Comprehensive Assessment of the Role of Risk in U.S. Agriculture. New York: Springer.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C.J., 2003. An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy 18, 267-288.

Leclère, D., Jayet, P.-A., de Noblet-Ducoudré, N., 2013. Farm-level Autonomous Adaptation of European Agricultural Supply to Climate Change. Ecological Economics 87, 1-14.

Lehmann, N., Finger, R., Klein, T., Calanca, P., Walter, A. 2013. Adapting crop management practices to climate change: Modeling optimal solutions at the field scale. Agric. Syst. 117, 55-65.

Lobell, D. B., Burke, M. B. 2008. Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. Environmental Research Letters 3, 034007.

Ministry of Agriculture and Food. 2011. Meld. St. 9 (2011-2012) Landbruks- og matpolitikken – Velkommen til bords. Ministry of Agriculture and Food. Oslo. [In Norwegian]

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grübler, A., Jung, T.Y., Kram, T., Lebre La Rovere, E., Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Riahi, K., Roehrl, A., Rogner, H.-H., Sankovski, A., Schlesinger, M., Shukla, P., Smith, S., Swart, R., van Rooijen, S., Victor, N., Dadi, Z., 2000. Emissions Scenarios Intergovernamental Panel on Climate Change Special Report. In: Nakicenovic, N., Swart, R. (Eds.). Intergovernmental Panel on Climate Change, Cambridge, UK, p. 570.

NIBIO (Norwegian Institute for Bioeconomy Research) (div.).Driftsgranskinger [Farm Account Data] Annual publication. Ås: Norwegian Institute for Bioeconomy Research.

Niles, M., Lubell, M. Van Haden, R. 2013. Perceptions and responses to climate policy risks among California farmers. Global Environmental Change 23: 1752-1760.

OECD. 2014. Agricultural Policy Monitoring and Evaluation 2014. Paris: OECD.

OECD and FAO. 2011. OECD-FAO Agricultural Outlook 2011-2020. Paris: OECD.

Olesen, J.E., Carter, T.R., Díaz-Ambrona, C.H., Fronzek, S., Heidmann, T., Hickler, T., Holt, T., Minguez, M.I., Morales, P., Palutikof, J.P., Quemada, M., Ruiz-Ramos, M., Rubæk, G.H., Sau, F., Smith, B., Sykes, M.T., 2007. Uncertainties in projected impacts of climate change on European agriculture and terrestrial ecosystems based on scenarios from regional climate models. Climatic Change 81, 123-143.

Pachauri, R.K., Reisinger, A., 2007. Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change, Geneva, Switzerland, p. 104.

Parry, M.L., Rosenzweig, C., Iglesias, A., Livermore, A., Fischer, G. 2004. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Global Environmental Change A 14: 53-67.

Persson, T., Kværnø, S., 2016. Impact of projected mid-21st century climate and soil extrapolation on simulated spring wheat grain yield in south-eastern Norway. Journal of Agricultural Science (Accepted, First View)

Persson, T., Höglind, M., 2014. Impact of climate change on harvest security and biomass yield of two timothy ley harvesting systems in Norway. The Journal of Agricultural Science 152, 205-216.

Persson, T., Kværnø, S., Høglind, M. 2015. Impact of soil type extrapolation on timothy grass yield under future climate conditions in southeastern Norway. Climate Research 65: 71-86.

Persson, T., Höglind, M., Gustavsson, A.-M., Halling, M., Jauhiainen, L., Niemeläinen, O., Thorvaldsson, G., Virkajärvi, P., 2014. Evaluation of the LINGRA timothy model under Nordic conditions. Field Crops Research 161, 87-97.

Ritchie, J.T., 1998. Soil water balance and plant water stress. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht/Boston/London, pp. 41-54.

Ritchie, J.T., Singh, U., Godwin, D.C., Bowen, W.T., 1998. Cereal growth, development and yield. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers Dordrecht, pp. 79-98.

Rötter, R.P., Höhn, J., Trnka, M., Fronzek, S., Carter, T.R., Kahiluoto, H., 2013. Modelling shifts in agroclimate and crop cultivar response under climate change. Ecology and Evolution 3, 4197-4214.

Rötter, R.P., Höhn, J.G., Fronzek, S., 2012. Projections of climate change impacts on crop production: A global and a Nordic perspective. Acta Agriculturae Scandinavica, Section A — Animal Science 62, 166-180.

Schapendonk, A., Stol, W., van Kraalingen, D.W.G., Bouman, B.A.M., 1998. LINGRA, a sink/source model to simulate grassland productivity in Europe. European Journal of Agronomy 9, 87-100.

Semenov, M.A., 2010. LARS-WG stochastic weather generator. Rothamsted Research.

Soussana, J.-F., Graux, A.-I., Tubiello, F.N., 2010. Improving the use of modelling for projections of climate change impacts on crops and pastures. Journal of Experimental Botany 61, 2217-2228.

Statistics Norway. 2010. Economic trends for Norway and abroad. Accounts and forecasts. Published December, 2.Oslo: Statistics Norway.

Stöckle, C.O., Donatelli, M., Nelson, R., 2003. CropSyst, a cropping systems simulation model. European Journal of Agronomy 18, 289-307.

Teixeira, E.I., Fischer, G., van Velthuizen, H., Walter, C., Ewert, F., 2013. Global hot-spots of heat stress on agricultural crops due to climate change. Agricultural and Forest Meteorology 170, 206-215.

Takayama, T. and Judge, G.G. 1971.Spatial and Temporal Price and Allocation Models.Journal of International Economics 3: 304-304.

Thornton, P.K., Ericksen, P.J., Herrero, M., Challinor, A.J., 2014. Climate variability and vulnerability to climate change: a review. Global Change Biology 20, 3313-3328.

Van Tongeren, F., Van Meijl, H., Surry, Y. 2001. Global models applied to agriculture and trade policies: a review and assessment. Agricultural Economics 26: 149-172.

White, J.W., Hoogenboom, G., Kimball, B.A., Wall, G.W., 2011. Methodologies for simulating impacts of climate change on crop production. Field Crops Research 124, 357-368.

Table 1. Trends in exogenous variables

Variable	Value	Source
Inflation	2.25% per annum	Statistics Norway (2010)
Population growth	1.01 % per annum	Statistics Norway (2010)
Technical progress	0.25% (1.0 %) input savings per annum at farm level [a] (food industry level)	Own assumption
Real interest rate	1.75 % per annum	Statistics Norway (2010)
Nominal world market prices	1.0 – 5.0 % per annum	OECD and FAO (2011)

[a] except labour and capital which are endogenously determined

Table 2. Average timothy (cv Grindstad) above-ground dry-matter yield (+ standard deviation) simulated for under 1961-1990 climate conditions and four climate projections for 2046-65 at four locations in Norway

	Ås	Sola	Tromsø	Værnes
	kg ha^{-1}			
	Baseline 1961-1990 climate			
	12620 (+2340) C[*]	15070 (+1400) C	8320 (+1370) D	14600 (+580) C
	2046-65 climate			
BCM2.0	15800 (+2530) A	16840 (+1410) B	12220 (+1140) A	16750 (+1420) B
CSIRO-M.k3.0	15920 (+2480) A	16590 (+1520 B	9670 (+3340) C	16710 (+1320) B
GISS-AOM	15920 (+2590) A	16730 (+1040) B	9860 (+550) C	14940 (+1140) C
HadCM3	13930 (+4370) B	20710 (+2620) A	11540 (+1320) B	17460 (+1650) A

[*] Means with different letters within columns are significantly different (P<0.05).

Table 3. Average simulated grain yield for three spring wheat cultivars (+ standard deviation) under 1961-1990 climate conditions and four climate projections for 2046-65 at Ås, Norway. Data from Persson and Kværnø (2015)

	Bjarne	Demonstrant	Zebra
		kg ha^{-1}	
		Baseline 1961-1990 climate	
	4538 (+568) C*	5251 (+616) C	5459 (+608) C
		2046-65 climate	
BCM2.0	4923 (+457) B	5684 (+513) B	6071 (+498) B
CSIRO-M.k3.0	4902 (+441) B	5652 (+497) B	6081 (+488) B
GISS-AOM	4910 (+431) B	5669 (+485) B	6063 (+413) B
HadCM3	5511 (+582) A	6342 (+651) A	6530 (+680) A

* Means with different letters within columns are significantly different ($P<0.05$).

Table 4. Animal production as simulated with Jordmod for mean yields and payment rates ("Certainty"), climate uncertainty ("C"), policy uncertainty ("P") and a combination of the latter ("C&P")

	Milk production (1 000 t)				Meat production (1 000 t)			
	Cer-tainty	Climate (C)	Policy (P)	C&P	Cer-tainty	Climate (C)	Policy (P)	C&P
Max		1 660	1 640	1 640		350	351	361
Min		1 607	1 615	1 607		333	334	333
Mean	1 640	1 628	1 627	1 624	338	339	340	346
Std.dev.		19.9	10.9	10.5		5.5	5.9	9.4

Source: Own calculations.

Table 5. Decomposition of animal production as simulated with Jordmod for mean yields and payment rates (“Certainty”), climate uncertainty (“C”), policy uncertainty (“P”) and a combination of the latter (“C&P”)

	Beef and sheep production (1 000 t)				Pork and poultry production (1 000 t)			
	Cer-tainty	Climate (C)	Policy (P)	C&P	Cer-tainty	Climate (C)	Policy (P)	C&P
Max		116	117	129		244	237	247
Min		105	102	93		217	221	217
Mean	115	111	112	113	222	228	228	233
Std.dev.		3.9	5.5	7.7		9.3	5.9	8.5

Source: Own calculations.

Table 6. Input use as simulated with Jordmod for mean yields and payment rates ("Certainty"), climate uncertainty ("C"), policy uncertainty ("P") and a combination of the latter ("C&P")

	Agricultural area (1 000 ha)				Labour use (1 000 person-years)			
	Cer-tainty	Climate (C)	Policy (P)	C&P	Cer-tainty	Climate (C)	Policy (P)	C&P
Max		928	932	963		45.2	46.3	48.2
Min		791	882	625		40.3	40.4	29.2
Mean	935	890	906	887	46.9	43.5	44.6	42.6
Std.dev.		51.7	18.6	71.0		1.8	2.1	4.1

Source: Own calculations.

Table 7. Profitability measures as simulated with Jordmod for mean yields and payment rates ("Certainty"), climate uncertainty ("C"), policy uncertainty ("P") and a combination of the latter ("C&P")

	Land rents (Nkr ha $^{-1}$)				Milk quota rents (Nkr kg $^{-1}$)			
	Cer-tainty	Climate (C)	Policy (P)	C&P	Cer-tainty	Climate (C)	Policy (P)	C&P
Max		4 471	5 963	6 324		4.48	4.63	4.76
Min		2 735	1 811	1 811		3.81	4.20	3.91
Mean	3 556	3 608	3 823	3 685	4.43	4.29	4.42	4.24
Std.dev.		577	1 428	1 235		0.24	0.14	0.18

Source: Own calculations.

Table 8. Welfare measures as simulated with Jordmod for mean yields and payment rates ("Certainty"), climate uncertainty ("C"), policy uncertainty ("P") and a combination of the latter ("C&P")

	Agric. income (1 000 Nkr person-year $^{-1}$)				Social welfare (bill Nkr)			
	Cer-tainty	Climate (C)	Policy (P)	C&P	Cer-tainty	Climate (C)	Policy (P)	C&P
Max		475	458	505		167	167	168
Min		410	426	401		164	165	163
Mean	421	437	439	444	166	166	166	166
Std.dev.		22.9	11.7	21.1		1.0	0.6	1.3

Source: Own calculations.